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We estimate the impact of minimum-wage increases on the quantity of labor demanded as measured by firms' vacancy postings. We use propriety, county-level vacancy data from the Conference Board's Help Wanted Online database. Our identification relies on the disproportionate effects of minimum-wage hikes on different occupations, as the wage distribution around the binding minimum wage differs by occupation. We find that minimum-wage increases during the 2005-2018 period have led to substantial declines in vacancy postings in at-risk occupations, occupations with a larger share of employment around the prevailing minimum wage. Our estimate implies that a 10 percent increase in the binding minimum- wage level reduces vacancies by 2.4 percent in this group. The negative effect is concentrated not exclusively in the routine jobs, but more in the manual occupations.

JEL: E24, E32, J30, J41, J63, J64.

Keywords: Minimum Wage, Vacancies, Hiring, Search and Matching.

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1. Introduction

Despite decades of research, the minimum wage remains a hotly debated issue among researchers and policymakers. Labor market behavior in the decade since the Great Recession has brought renewed energy to the debate over raising the minimum. Despite the unemployment rate being at its lowest level in five decades, wage growth remains anemic and labor force participation is low by the standards of recent history, especially among young and lower-skilled workers. In this environment, a broad-based minimum-wage increase presents itself as an attractive policy tool to boost wages. In a competitive labor market, theory predicts that such a wage boost might happen at the expense of a loss in employment. This issue has motivated a large literature on the effects of the minimum wage on employment (see Card and Krueger (1994, 2000), Neumark and Wascher (1992, 2008), among others).

This paper contributes to this literature in several ways. We provide evidence for the effect of minimum-wage changes on vacancies, an important labor market variable of interest. Since recruitment effort is an important factor in determining employment changes, understanding the impact on vacancy postings might shed additional light on the aforementioned debate regarding employment effects of minimum-wage changes. We use vacancy data at the county level for 2-digit occupation groups at a quarterly frequency to study the effect of minimum wages. Our identification strategy relies on the assumption that workers in some occupations are less vulnerable to minimum-wage increases than others. We formalize this identification by analyzing the wage distribution by occupation at the state level from the Current Population Survey (CPS).[1] Based on our analysis of occupational wage distributions, we identify several occupations that we refer to as *at-risk occupations*. At-risk occupations are those with a larger share of employment around the prevailing minimum wage. Our empirical specification relies on identifying the growth in vacancies for at-risk occupations relative to other occupations around the time the minimum-wage changes in each state and relative to the growth in national vacancies in the at-risk occupation group.

We find significant negative effects, implying that a 10 percentage increase in the level of a binding minimum wage reduces vacancies in at-risk occupations by about 2.4 percent. Moreover,

[1] This approach is related to recent work by Cengiz et al. (2019), where authors explore the effect of minimum wage changes at different points of the wage distribution.

we find that this baseline result is driven by a strong preemptive response by the firms, which cut vacancies in advance of the minimum-wage change. We find mixed evidence about the vulnerability of routine jobs to minimum-wage increases. Instead, we find strong evidence that manual occupations in the at-risk group are responsible for the significant negative effect found in the baseline.

Our paper also has a methodological contribution about the empirical approach for minimum-wage research. Our results seem to be also robust to more specific local controls as we find almost identical estimates using adjacent border-counties (as in Dube et al., 2010). We argue that this has a lot to do with the flexibility our empirical specification affords us. In particular, our empirical design allows us to control for arbitrary county level trends in different occupations that has nothing to do with minimum-wage changes. The adjacent border-county design for minimum-wage research proposed by Dube et al. (2010), was primarily motivated by the absence of these trends in earlier work by Neumark and Wascher (1992, and 2008). Our methodology is immune to this criticism, thereby delivering very similar effects in the adjacent border-county setup. In contrast to Dube et al. (2010), though, we find significant negative effects even with the adjacent border-county setup.

2. Minimum Wage and Vacancies in the Related Literature

2.1. Theory

In both the standard neoclassical and frictional models of the labor market, the increase in the binding minimum wage leads to a decline in the quantity of labor demanded, unless the labor demand for minimum-wage jobs is inelastic. In the standard neoclassical model, higher minimum wage leads to movement left and up the labor demand curve (Stigler (1946)), which leads to a rapid decline in employment. Adjustment costs migh slow the transition to a new employment level (Oi (1962), Hamermesh (1989), Diamond (1981) and Acemoglu (2001)). In the frictional models of the labor market, an increase in the minimum wage also leads to a decline in the number of vacancies due to an increase in the marginal costs. The effect of the minimum wage on hiring (i.e., job creation) is ambiguous because while vacancies decline, the job seeker input increases - either due the increase in the number of job seeker or search efficiency (Van den Berg and Ridder (1998), Flinn, (2006, 2010), Rocheteau and Tasci (2007, 2008), Gorry (2013), Sorkin (2015)).

The task content of the job that is facing a higher minimum wage might also play a role. If the demand for labor for the minimum-wage type jobs is inelastic, the increase in minimum wage has no effect on the quantity of labor demanded, at least in the short run. Routine labor can relatively be easily automated; non-routine labor is hard to automate and thus demand is less elastic. There is a recent literature which studies richer effects of minimum-wage increases by allowing capital-labor substitutability. Hemous and Olsen (2018) show that increases in the cost of low-skill labor leads to an increase in automation which in turn increases demand for high-skill workers but reduces demand for low-skill workers. Bauducco and Janiak (2018), using a calibrated search and matching model, find that a relatively large increase in the minimum wage leads to a decrease in employment but to an increase in capital and output. Our results indicate that, the negative effects we find for vacancies are not driven by routine occupations, but manual ones. Hence, our paper provides some evidence in contrast to this literature.

2.2. Empirics

Empirical literature has primarily focused on the effect of the minimum wage on employment. The literature is highly contentious, with the estimates ranging from zero (Card and Kruger, 1994) to large negative effects (Neumark and Wascher, 2008).

Estimation of the effect of state-level minimum-wage hikes presents a few challenges. The state-level real minimum-wage hikes have “saw tooth” pattern because over time nominal minimum-wage hikes are eroded by inflation (Neumark and Wascher, 1992). This saw-tooth pattern, adjustment costs and long-run planning horizons complicate the analysis. Recently, Meer and West (2016) argue that the minimum-wage hikes might effect not necessarily the level but the growth of employment.[2] They argue that the effect on employment level is confounded by adjustment costs and existing approaches in the literature are stacked against finding an effect on the level of employment. They find that unequivocally higher minimum wage leads to lower rates of job growth. In particular, a 10 percent increase in the minimum wage causes a half percentage point reduction in the rate of job growth. The effect is not permanent though, as it gets eroded by inflation. They find that most of the decline in the net job growth is driven primarily by reduction

[2] Building on the treatment effects studies (Lee and Solon, 2011; Wolfers, 2006), Meer and West (2016) argue that if the treatment effect is not a discrete level shift in employment on impact but rather a change in the slope (i.e., in the rate of net employment growth), then studies that control for jurisdiction-specific trends might suffer from an attenuation bias.

in job creation by contracting establishments as opposed to increases in job destruction by contracting establishments. The effect on vacancies that we study is at the core of this margin.

A large literature focuses on the effects of minimum-wage increases on worker groups that are most likely to be affected – teenagers, older, low-skill or low-wage workers. For example, Clemens and Wither (2019) estimate the effect of minimum-wage increases on low-skilled workers' employment and income trajectories and find that binding minimum-wage increases had significant, negative effects on the employment and income growth of targeted workers. On the other hand, Currie and Fallick (1996) focus on the reemployment probabilities of the youth in NLSY to estimate the employment effect of the minimum-wage changes in 1979 and 1980 for low-wage workers.

Several recent empirical papers focus on the heterogeneity of the minimum-wage effect across types of jobs. Technological advances and decline in the price of labor-substituting technology have made capital cheap relative to a substitutable labor. Lordan and Neumark (2018) find that increasing the minimum wage decreases significantly the share of automatable employment held by workers with high school diploma or less. They also find that job opportunities improve for high-skill workers in the industries where a high share of low-skill workers are employed in automatable jobs. That is, the minimum wage spurs substitution away from low-skill workers in automatable jobs. Aaronson and Phelan (2019) find that increases in the cost of low-wage labor, via minimum-wage hikes, lead to relative employment declines at routine cognitive occupations but not routine manual or non-routine low-wage occupations. This suggests that low-wage routine cognitive tasks are susceptible to technological substitution. While the short-run employment consequence of this reshuffling on individual workers is economically small, due to concurrent employment growth in other low-wage jobs, workers previously employed in routine cognitive jobs experience relative wage losses.

Other authors study the impact on the minimum wage on other important aspects of labor relationships. Aaronson, French, and MacDonald (2008) find that restaurant prices unambiguously rise after minimum-wage increases are enacted.[3] In this paper, we addresses some of this

[3] Among other aspects are quality of newly created matches, job ladder dynamics, etc. See Flinn (2006) and Neumark and Wascher (2008) for detailed reviews.

underlying heterogeneity by analyzing the differential effects on types of occupations by their routine-task content.

3. Data

3.1. Vacancies

Our main labor market outcome variable is the county-level vacancy (job opening) data reported by the Conference Board (2017) as part of its Help Wanted OnLine (HWOL) data series. HWOL provides a monthly snapshot of the quantity of labor demanded at detailed geographical (state, metropolitan statistical area, and county) and occupational (six-digit SOC and eight-digit O*Net) levels since May 2005.[4] For the period in question, HWOL represents the bulk of the advertised job openings, as print advertising declined in importance.[5]

HWOL covers roughly 16,000 online job boards, including corporate job boards, and aims to measure unique vacancies by using a sophisticated deduplication algorithm that identifies unique advertised vacancies based on several ad characteristics such as company name, job title/description, city, or state. HWOL is not the only source of data on job openings, though. The Bureau of Labor Statistics (BLS) publishes nationally representative data, the Job Openings and Labor Turnover Survey (JOLTS), which also measures vacancies. However, HWOL's detailed geographic- and occupation-level coverage makes it uniquely attractive for our analysis. JOLTS' publicly available data files do not have more detailed coverage than census regions and lack any information on occupational characteristics. This additional level of granularity in the HWOL data provides us with a novel opportunity to implement our identification strategy.

The sample period for the HWOL data we use in this paper ranges from May 2005 to October 2018. This provides us with the coverage of the period with various minimum-wage increases at the state and federal level. Throughout our sample period, about 36 percent of all job postings are for occupations that fall into the at-risk group of occupations, which are more susceptible to minimum-wage hikes. Table 1 shows some descriptive statistics for the vacancy data over time by occupational group. We see that at-risk occupations had lower levels of job

[4] For a detailed description of the measurement concepts and data collection methodology, please see Conference Board (2017). *The Conference Board Help Wanted OnLine® (HWOL) at* https://www.conferenceboard.org/data/-helpwantedonline.cfm.

[5] In fact, HWOL started as a replacement for the Conference Board's Help-Wanted Advertising Index of print advertising.

openings over the entire sample. However, vacancies in both at-risk and no-risk occupations present a procyclical pattern over the business cycle, slightly declining during the recession and rising over the course of the expansion.

Our identification strategy relies on identifying occupations that have a large mass near the prevailing minimum wage in the wage distribution. We describe this process in detail below (in section 4.1). This process yields a small set of 2-digit occupations that we will indicate as at-risk occupations. These occupations are: Food processing and servicing related occupations (SOC-35), building and grounds cleaning and maintenance occupations (SOC-37), personal care and service occupations (SOC-39), sales and related occupations (SOC-41), office and administrative support occupations (SOC-43) and transportation and material moving occupations (SOC-53). The overall share of employment in these occupations constitutes about 42 percent of aggregate employment in the U.S., slightly higher than the share of vacancies posted. Even though we have data at the monthly frequency, in this paper, we focus on the quarterly data, aggregated from the monthly series. HWOL data include the stock of vacancies as well as new job postings (less than 30 days-old), allowing us to potentially analyze the effects of minimum-wage increases on stocks and flows separately.

3.2. Minimum Wage Data

We construct a quarterly data set of state-level effective minimum wages. To construct this, we start with the state-level mandated minimum wage (if such a state mandate exists), combine this information with the federal wage, and calculate the effective minimum wage for each date as a maximum of the two. We heavily rely on the compilation of the effective minimum-wage data for states and sub-state jurisdictions (such as cities and counties) in Vaghul and Zipperer (2016). Their sample ends in mid-2016. For the remainder of the sample period, we thoroughly searched for state-level effective minimum-wage changes on the relevant state agency's websites and the information provided by the BLS.

The primary data from Vaghul and Zipperer (2016) are available at the daily frequency to specifically identify the effective date of minimum-wage change. When we aggregate our minimum-wage measure to the quarterly frequency, we assume the higher minimum-wage level as the binding one for the quarter. Our results are robust to slightly different variants of this aggregation. Moreover, in most cases, minimum-wage increases took effect at the beginning of a month and often times at the beginning of a quarter.

As Figure 1 shows, our sample period covers significant variation in effective minimum wages at the state-level. Early in our sample period, federal minimum wage rose gradually from \$5.15 per hour to \$7.25 per hour. The first hike in the federal minimum-wage level in 2007 was preceded by a significant decline in the number of states with effective minimum wages at the federal level. At the beginning of the sample in 2005, there were 37 states in the US which did not have a binding state-level minimum wage. Within a few years, this number declined to 18, as more states enacted minimum-wage laws bringing their effective minimum wage to levels above the prevailing federal level. Federal minimum wage has not changed since 2009, but the state level variation, if anything, increased since then. As Figure 2 shows, the highest binding minimum wage at the end of 2018 stands at \$13.25 per hour (in DC), twice the level of the federal minimum wage.

In our sample, we not only have a large geographical variation in the level of the minimum wage, but also a sizeable variation in the magnitude of changes. There are about 300 effective minimum-wage hikes in our data, ranging between a 0.5 percent increase to more than 34 percent. The median percent change in the effective minimum wage is right around 7 percent. In our baseline identification, we consider the pool of workers who earn at or below 110 percent of the prevailing minimum wage in a specific location, as potentially vulnerable workers to minimum-wage increase. Almost 60 percent of all minimum wage increases in our data fit this pattern (Figure 3). We believe that this underlying variation in the binding minimum wage across the U.S. states and the variation in the magnitude of the changes provide us with a great opportunity to identify the effects of minimum-wage hikes.

3.3. Other Variables

Our identification scheme heavily relies on the assumption that some occupations are more exposed to minimum-wage increases, as the wage distribution can be more skewed to the left. As the size of employment around the minimum- wage increases, more workers will be affected by the proposed minimum-wage increase. In order to implement this identification strategy, we need to analyze hourly wage distribution by 2-digit occupations. We accomplish this by using the data from the Current Population Survey (CPS). More specifically, we focus on working individuals of age 16 and above and exclude those who are self-employed or working without pay, from the fourth and the eighth month in the sample, for which there is information about wages. We compute hourly wage data directly by using the hourly wage measure in the CPS data. When that is not available, we rely on weekly hours worked and weekly wage data to compute an hourly wage.

Once we have data on hourly wage at the individual level, we can analyze wage distributions by occupation at the state level. Combining this information with the data on state-level binding minimum wage helps us gauge to what extent a particular occupation might be affected by the minimum-wage increase. In order to quantify the size of the at-risk pool, we adapt a threshold rule of 10 percent relative to the minimum wage. In other words, we consider an occupation to be in the at-risk group, if the fraction of employment at or below 110 percent of the prevailing minimum wage is large enough. This is partly informed by the distribution of the minimum-wage increases in the sample (Figure 3). In order to pin down the relevant metric for the size of the at-risk pool, we also adapt another threshold of 5 percent. Specifically, we designate an occupation as in the at-risk group if at least 5 percent of the overall employment for workers earning at or below the 110 percent of the prevailing minimum wage (in a state) is in that occupation. We assess whether our results are robust to variations on these two threshold levels.

Following this methodology leads us to pick six different occupations as at-risk occupations for minimum-wage changes. The 5 percent threshold comes out as naturally from the wage distributions. As Table 2 shows, there is a clear clustering separated by 5 percent employment share. Table 2 presents employment shares of workers in occupations (averaged across states) for a given year who earn at or below 110 percent of the prevailing minimum wage. The average share for the whole sample is about 4.5 percent, whereas the median share stands at 2.8 percent. We find the resulting classification reasonable and intuitive. Most of the occupations in the at-risk group are low-wage service sector jobs. Food processing and servicing related occupations have the largest share of at-risk pool, on average about 21 percent, followed by sales related occupations at 14.2 percent and office and administrative support occupations by 7.9 percent. Despite some variation over the years in terms of employment shares, the 5 percent-rule is remarkably robust over time.

In some of our regressions, we control for additional location-specific variables. Specifically, we use log of the state or county-level population, employment or unemployment rate. When needed, this data from Local Area Unemployment Statistics (LAUS) program is pulled from HAVER Analytics.

4. Empirical Approach and Results

This section describes our identification strategy in detail and presents our empirical results.

4.1 Identification strategy

Our preferred empirical setup is essentially a triple-difference regression approach. We would like to capture the effect of minimum-wage increases on vacancy creation by the following panel regression.

$$(1) \qquad \log(V_{i,o,t}) = \alpha_{i,o} + \mu_{o,t} + \gamma_{i,t} + \beta \log(MW_{i,t}) * At\ Risk_{i,o} + \varepsilon_{i,o,t}$$

In specification (1), the outcome variable that we are interested in is the log of (the number of) vacancies in county i, occupation o, at time t. Variable $At\ Risk_{i,o}$ is an indicator function identifying whether occupation o in location i is one of the occupations with a large employment share due to workers earning at or below 110 percent of the prevailing minimum wage.[6] The parameter of interest is β and $\alpha_{i,o}$ is a county-occupation fixed effect, $\gamma_{i,t}$ is a county-time fixed effect (measured quarterly), and $\mu_{o,t}$ is an occupation-time fixed effect.

The coefficient of interest, β, is identified from the growth in vacancies for at-risk occupations relative to others around the time when minimum-wage changes in that state and relative to the growth in national vacancies in the at-risk occupations. The power of the identification comes from the ability to control for arbitrary county specific trends in posted vacancies in the form of county-by-time fixed effects, $\gamma_{i,t}$. Note that, in contrast, a typical empirical approach in the minimum-wage literature is to identify a narrowly defined group, such as teenage employment, or restaurant workers, and run the following regression :

$$(2) \qquad \log(E_{i,t}) = \alpha_i + \gamma_{,t} + \beta \log(MW_{i,t}) + \varepsilon_{i,t}\ ,$$

where $E_{i,t}$ stands for employment in location i, at time t. We prefer our specification in equation (1) over this approach for several reasons. First, our preferred approach controls for occupation

[6] Note that in our baseline specifications we assume that this variable, $At\ Risk_{i,o}$ is independent of i.

and county-specific trends in vacancies within a specific location, as well as the unobserved variation in occupational-demand across locations. Second, we think our specification is equivalent to effectively running a placebo test. There are occupations in which only a small fraction of workers are employed at wage levels that are anywhere close to a prevailing minimum wage. Legal occupations, for instance, is one such example. We find that this occupation employs only 1.3 percent of the workers who earn at or below 110 percent of the prevailing minimum wage throughout our sample. Hence, by effectively comparing the effects of the minimum-wage increase on at-risk occupations relative to those such as Legal occupations, our empirical design provides us with a better identification of the causal effect.

Like most of the empirical literature, we will focus on the short-term effects of minimum-wage increases. However, due to the nature of the variable of interest (vacancies), and the typical announcement of minimum wage legislation both at the federal and state-level, we expect that there might be some forward-looking response in firms' vacancy posting. In order to analyze this potential effect, we also run an empirical specification, where we introduce dynamic leads and lags of the effective minimum wage into equation (1).

Finally, following the influential work by Dube et. al. (2010), we also implement a an adjacent border-county specification of our main identification strategy. The main idea here is to find a better control group to capture the true treatment effect of minimum-wage increases. The assumption is that counties along the state borders might have more similar labor market conditions but exogenously different state-level binding minimum wages. This specification also allows us to control for arbitrary time-varying unobserved heterogeneity between the treatment and control groups on different sides of the state border.

Specifically, in our context, implementing the contiguous-county specification implies running the following regression

$$(3) \quad \log(V_{i,o,p,t}) = \alpha_{i,o} + \gamma_{o,p,t} + \beta\, log(MW_{i,t}) * At\ Risk_{i,o} + \varepsilon_{i,o,p,t}.$$

where p stands for a county-pair. However, we can still include very granular fixed effects for local labor market conditions by estimating the minimum wage's effect using only contiguous counties along state borders, which allows us to include a county-pair-by-time-by-occupation fixed effect.

4.2 Results

Baseline Estimates

We estimate our preferred specification in (1) with the panel data we constructed using HWOL and the minimum-wage data we compiled building on Vaghul and Zipperer (2016). In this specification, the unit of observation is an occupation in a county in a particular quarter. Table 3 reports our baseline estimation results. The first three columns report the estimated impact of minimum wage on total vacancies (i.e. the stock) and the remaining columns report the estimated coefficients for new job openings (vacancies less than 30-days old).

As column (1) in the Table 3 shows, we find a negative and statistically significant effect of minimum-wage increases on vacancies. The estimated elasticity of vacancies for at-risk occupations are economically meaningful as well: $\beta = -0.24$. In other words, a minimum-wage increase of 10 percent reduces vacancies by about 2.4 percent for the occupations that employ more workers who are in the at-risk pool. To provide some context for this magnitude, consider the aggregate decline in vacancies by different occupations during the Great Recession. Average decline in 2-digit occupations has been 20 percent during the recession[7]. Considering that the Great Recession was one of the largest economic shocks that ever hit the U.S. economy, a decline of 2.4 percent in response to a minimum-wage increase by 10 percent is very significant.

It is natural to think that vacancy posting behavior by firms have some forward-looking element. In the context of frictional labor markets, where filling a vacancy takes time and resources, vacancies respond to shocks first, relative to other equilibrium variables such as unemployment or employment (Mortensen and Pissarides, 1994). On the other hand, most minimum-wage increases are anticipated and often legislative debate at the state level can precede the actual implementation by a few quarters.[8] Hence, we would like to explore if this negative impact of minimum-wage increase is led by a preemptive adjustment by the firms before the minimum-wage change is enforced. We add dynamic leads and lags to our baseline specification in column (1).

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[7] From December 2007 to Jul7 2019.

[8] See the following blogpost on the website of National Conference of State Legislatures: http://www.ncsl.org/blog/2018/08/23/state-minimum-wage-developments.aspx.

Column (2) of Table 3 shows that when we add one lag and one lead of the minimum-wage interaction term, contemporaneous effect declines substantially and becomes insignificant. This, however, is more than offset by the response of vacancies (today) to a minimum-wage increase in the next quarter. The coefficient further declines to -0.36, indicating a much larger elasticity for vacancies to a proposed minimum-wage increase one quarter ahead. The cumulative effect still is significant and is around -0.28. Column (3) in Table 3 extends this to a larger window around the minimum-wage change and confirms our expectation that most of the negative effects are induced in advance. Extending this dynamic-lag structure beyond a two-quarter window runs the risk of confounding the lagged-effects of minimum wage changes with the anticipatory effects induced by frequent minimum-wage changes that fall with a four-quarter window. Such frequent minimum wage-changes are present in our sample.

The rest of Table 3 also confirms that the minimum-wage increases are associated with significant declines in new job openings for the at-risk occupations. The magnitudes for new vacancies are not very different from the estimated magnitudes for total vacancies, ranging between -0.22 to -0.29. For the rest of the analysis we keep our focus on total vacancies.

Standard Diff-in-Diff Estimates

We believe our preferred specification spelled out in equation (1) and presented above has many advantages. We can essentially use a lot of variation in the occupation composition of vacancy postings and each occupation's level of exposure to minimum-wage increases in a nested model where we can then introduce many granular fixed effects to control for other arbitrary unobserved variation that has nothing to do with minimum-wage changes. Here, we would like to evaluate, to what extent being able to have these granular fixed effects in the regression matters for our results. To do so, we estimate specification (2) separately with at-risk occupations and others by aggregating the level of vacancies in each group. In this exercise, the outcome variable is the level of vacancies in a county in quarter t, for a group of occupations. Since we do not have the flexibility of our preferred specification, we can only control for time invariant county-specific factors (α_i) and aggregate time varying trends ($\gamma_{,t}$).

Table 4 presents our results from this exercise. As column (1) highlights, we find basically no effect from a minimum-wage increase for total vacancies in the group of at-risk occupations if we follow a typical Diff-in-Diff approach. We contend that this has a lot to do with the fact that we do not control for time-varying unobserved variation at the county-level that is ignored due to lack of county-by-time fixed effects. To see this point, we add a county-level control variable, the unemployment rate, to the right hand-side. In principle, the coefficient estimate for this control essentially gives us the Beveridge curve relationship at the local level. That is, over the long-run, unemployment and vacancies are negatively correlated, which is corroborated by the estimate of -0.039 in column (2). If we control for the past history of the labor market, the coefficient estimate gradually turns negative and approaches the baseline estimates from Table 3.

A similar story emerges from columns (5) through (8). In the absence of any controls, total vacancies in occupations that do not employ many workers near the minimum-wage threshold increase with a higher minimum wage, with a statistically significant and large elasticity estimate of 0.42. As the rest of the table implies, this spurious correlation is mostly due to the fact that we are not controlling for county and occupation specific trends in the local labor market. Since nominal minimum wage is monotonically increasing for every location in our sample and there is a general upward trend in vacancies, ignoring underlying local trends could easily yield a positive effect. This exercise highlights the important methodological issue we raise in this paper. By ignoring granular local effects, our estimation results seem to be biased towards zero for the impact of minimum wages on vacancies. Conceptually, this bias might easily be present in the empirical work focusing on employment effects of minimum-wage changes.

Adjacent Border-County Sample

In an influential study, Dube et al. (2010) propose an empirical specification to estimate the impact of minimum wages on employment using data from counties along state-borders. They argue that counties across the border that did not have a minimum-wage change could be a better control group. The assumption is that the unobserved heterogeneity between adjacent border-counties will be less pronounced than the average county in each state. They also present this as a general approach to incorporate multiple individual case-studies that had dominated part of the minimum-wage literature at the time (Card and Krueger, 1994, 2000). Motivated by these arguments, we want to estimate the effects of minimum-wage changes on vacancies using a similar border-county sample as well.

Table 5 presents our estimation results from this specification and shows that the estimated coefficient from this sample is almost identical to the baseline specification, with an estimate for

$\beta = -0.25$. Adding leads and lags of interaction terms change the coefficient slightly, but overall conclusions from our baseline specification are confirmed in this sample as well. Our estimated negative effect of a minimum-wage increase on vacancies seem to be quite robust to different empirical approaches in this regard.

Heterogeneous Effects across Occupations

Our empirical approach did not discriminate between different occupations within the at-risk group. This might be misleading if the task content of an occupation matters for firms in response to a minimum-wage hike. For instance, a firm posting a vacancy for an occupation primarily involving routine tasks, might expect a potential minimum-wage increase and adopt labor-saving technologies more frequently or intensely than its competitor who seeks to hire workers for occupations with primarily non-routine tasks (Lordan and Neumark, 2018). We explore whether our data reveal anything on this question by focusing on detailed 2-digit occupations based on this feature of them.

The routine vs. non-routine distinction and further classification into routine manual, routine cognitive, non-routine manual and non-routine cognitive categories follow Jaimovich and Siu (2012) and Tuzemen and Willis (2013). From our list of at-risk occupations; food processing and servicing related occupations (SOC-35), building and grounds cleaning and maintenance occupations (SOC-37), personal care and service occupations (SOC-39) are considered non-routine manual occupations. Sales and related occupations (SOC-41), and office and administrative support occupations (SOC-43) constitute the routine cognitive group. Finally, the only occupation in the at-risk group that fits the routine manual category is transportation and material moving occupations (SOC-53).

Table 6 replicates the baseline regression result in column (1) for convenience along with new results exploring the finer classifications for the task content of the occupation. Column (2) confirms the negative and statistically significant effects of the minimum-wage changes on vacancies. This negative effect does not seem to be led by the routine occupations in the at-risk group. Column (3) refines this dimension further and reveals that manual occupations, not necessarily routine ones, are negatively impacted by the minimum-wage changes.

5. Robustness

Our results clearly show that minimum age increases are associated with a large and significant decline in job openings for at-risk occupations. Our definition of at-risk occupation relied on two thresholds that we picked. Even though we think we have good arguments for the legitimacy of the thresholds, we want to analyze how robust our results are to these thresholds. We also examine how a particular measurement issue in the vacancy data affects our results.

Since our identification strategy is ultimately about the categories of at-risk occupations, one simple way to check for the robustness of our results with respect to this definition is to remove occupations in the at-risk group one at a time and rerun our baseline regression. Note that, this in a sense a test for the robustness of our 5 percent threshold. Dropping building and grounds cleaning and maintenance occupations, for instance, effectively brings the threshold to 6.5 percent from 5.

Figure 4 presents point estimates and the 95 percent confidence intervals around them as we remove one occupation from the at-risk group at a time. None of these exclusions seem to be changing our baseline result at all. The lowest elasticity we get falls to -0.17 (when transportation is excluded) and even then, our baseline estimate of -0.24 falls into the confidence band. Hence, we conclude that our baseline results are robust to variations of our basic definition of the at-risk occupation group.

Another potentially unique challenge in our analysis is posed by the nature of the HWOL data at the granular level that we use. In principle, there may not be any vacancies posted for a certain 2-digit occupation category in a sparsely populated county in our sample. In fact, this is somewhat common. Since we take the logarithmic transformation of the vacancy data, zeros will drop from the sample. Incidentally, if in the following quarter this is followed by one posting, that county-occupation observation will be back in the sample. Hence, one might worry that we are getting some spurious correlation driven by these somewhat arbitrary changes. We can test how robust our results are for this measurement issue with two possible alternatives. We present these two alternatives along with the baseline result for convenience in Table 7.

The first alternative is to transform the level of vacancies by the inverse hyperbolic-sine function. This transformation avoids dropping zero observations from our estimation sample. As column (2) shows, this amounts to an additional one-million observation, quite a large increase relative to the baseline. However, it barely affects our baseline result, yielding a slightly lower elasticity of -0.25. Another transformation we consider is effectively renormalizing the zero observation by using $\log(V_{i,o,t} + 1)$ for our outcome variable, instead of $\log(V_{i,o,t})$. This transformation also does not change the main conclusion, as the last column of Table 7 shows. We conclude that our results are robust to this particular measurement issue with the vacancy data as well as the definition of at-risk occupations.

5. Conclusions

In this paper, we have proposed a novel identification strategy to estimate the impact of minimum-wage increases on vacancies, a labor market variable that has not been studied in the large minimum-wage literature. Our identification strategy builds on the idea that not all occupations will be similarly affected by minimum-wage increases. There are occupations in which very few workers work at or near the prevailing minimum-wage level. Intuitively, one should not expect to see any direct effects from a minimum-wage increase in this case. We formalize this and identify six 2-digit occupations as potentially at-risk occupations. Our results point to statistically significant and large negative effects. Vacancies posted for occupations in the at-risk group face 2.4 percent drop in response to a 10 percent rise in the prevailing minimum wage relative to other occupations. This baseline result seems to be driven by strong preemptive response by the firms, cutting vacancies in advance of the minimum-wage change. We find mixed evidence about the vulnerability of routine jobs to minimum-wage increases. Instead, we find strong evidence that manual occupations among the at-risk group are behind the significant negative effect found in the baseline.

The literature on minimum wage's employment effect has been contentious, arguing for different empirical designs and delivering sometimes starkly different estimation results. Studies that use cross-geographical variation with fixed-effects mostly point to somewhat small but significant negative effects (Neumark and Wascher, 1992, 2008). On the other hand, event studies involving neighboring jurisdictions that focus on individual minimum-wage episodes (Card and Krueger, 1994, 2000; Dube et al., 2007) or consider a whole set of them (Dube et. al., 2010) find no significant negative effects on employment. We show in our paper that both methodologies provide consistently negative and significant effects for the case of vacancies. Either using cross-county variation along with occupational heterogeneity in terms of exposure to minimum-wage hikes or relying on adjacent border county regression specification provides us with similar estimation results.

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TABLE 1: DISTRIBUTION OF VACANCIES By OCCUPATION – COUNTY LEVEL

	At-Risk Occupations (Log Vacancies)			No-Risk Occupations (Log Vacancies)		
Year	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
2005	8,884	3.26	2.17	9,226	3.80	2.08
2006	12,063	3.28	2.21	12,340	3.87	2.12
2007	11,994	3.29	2.30	12,362	4.01	2.15
2008	11,980	3.33	2.28	12,401	4.11	2.10
2009	12,044	3.28	2.17	12,419	4.06	1.99
2010	12,194	3.46	2.17	12,456	4.20	2.01
2011	12,245	3.71	2.16	12,449	4.35	2.01
2012	12,370	4.02	2.06	12,488	4.57	1.98
2013	12,420	4.22	2.02	12,510	4.63	1.98
2014	12,456	4.24	2.08	12,523	4.75	1.95
2015	12,521	4.44	1.99	12,516	4.83	1.95
2016	12,506	4.40	1.94	12,520	4.78	1.95
2017	12,434	4.17	2.03	12,521	4.68	1.99
2018	12,458	4.26	1.96	12,519	4.70	1.95
All Years	168,569	3.83	2.16	171,250	4.40	2.04

Note: This table presents the first and second moments for vacancies at the county-level over time. We sum all vacancies within occupations that are in the at-risk group (SOC-35, SOC-37, SOC-39, SOC-41, SOC-43, and SOC-53) and present the log of that sum. Similarly for the reminder of the occupations that are not in the at-risk group.

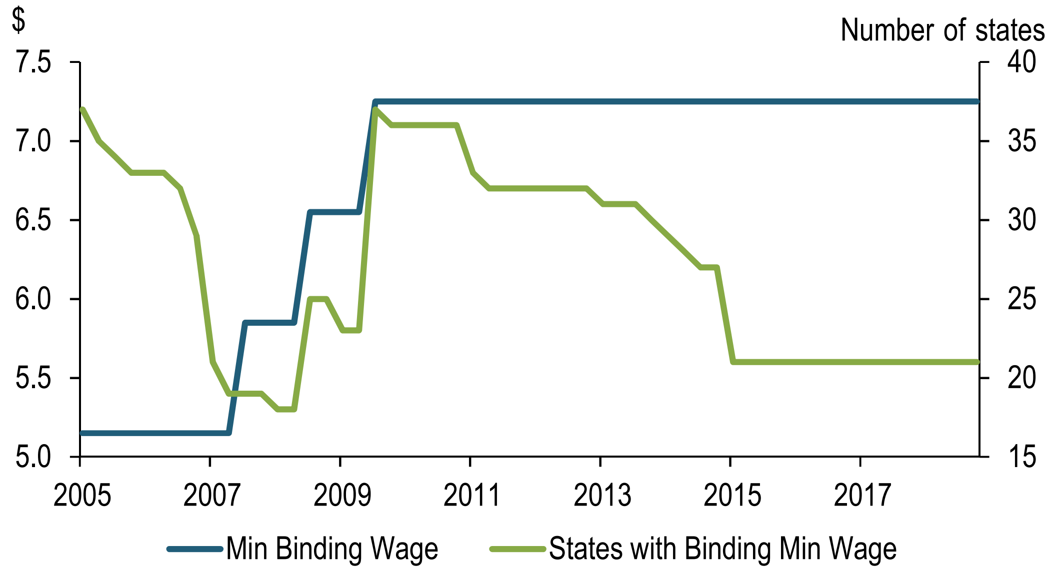

Figure 1: Federal minimum wage level and the number of states that has a binding minimum wage level that is higher than the federal one.

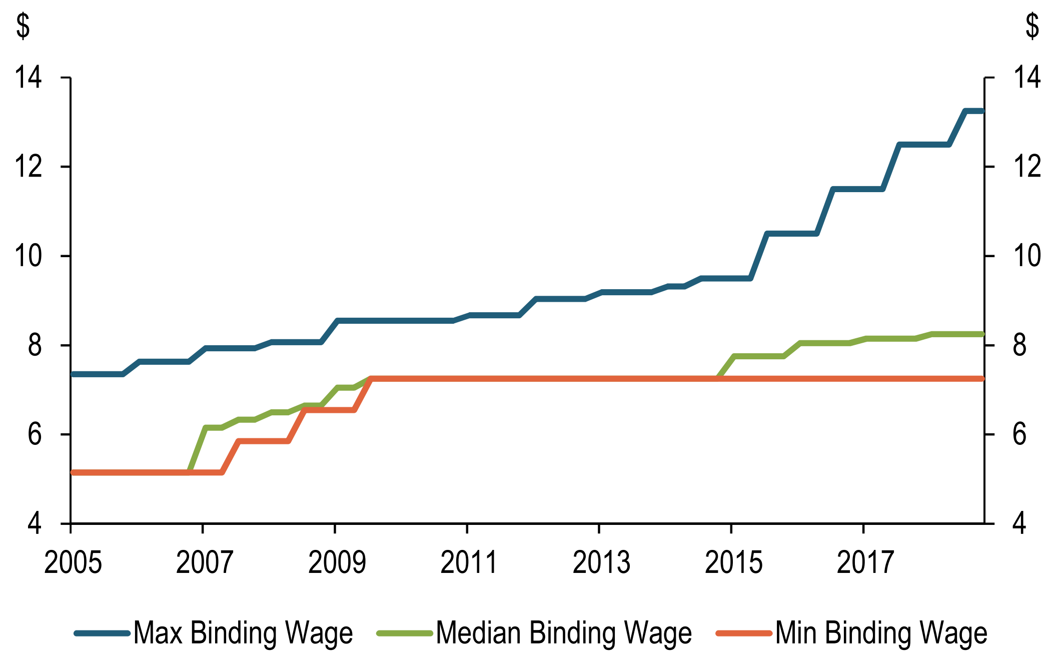

Figure 2: The range of state-level minimum wages. Minimum binding minimum wage is the effective federal minimum wage.

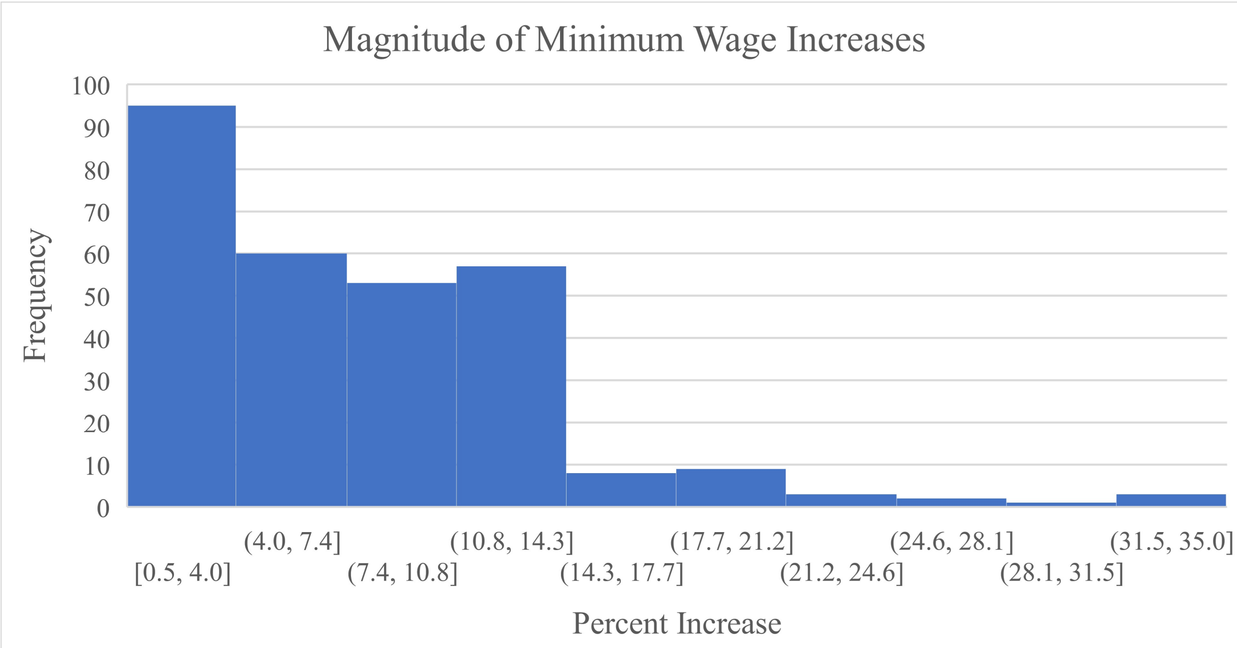

Figure 3: Distribution of minimum wage changes

TABLE 2: FRACTION OF AT-RISK EMPLOYMENT BY OCCUPATION

SOC	Occupation	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
11	Management	2.3	2.8	2.1	2.4	2.2	2.0	2.5	2.3	2.3	2.4	2.3	2.2	2.6	2.6
13	Business	2.1	2.0	1.8	1.7	1.6	1.4	1.6	1.5	1.4	1.5	1.7	2.1	1.6	1.8
15	Computer	1.5	1.8	1.6	1.4	1.3	1.2	1.3	1.5	1.4	1.6	1.2	1.7	1.4	1.3
17	Architecture	1.8	1.6	1.2	1.3	1.2	0.9	1.3	1.3	1.2	1.3	1.6	1.6	1.3	1.7
19	Life	2.1	1.9	1.2	1.3	1.2	0.8	1.1	1.5	1.7	0.9	1.6	1.4	1.4	1.0
21	Community	1.9	1.7	1.5	1.6	1.4	1.6	1.1	1.3	1.4	1.4	1.4	1.5	1.6	1.7
23	Legal	2.0	1.2	1.5	1.1	1.0	1.1	1.2	1.4	1.2	1.4	1.3	1.1	1.1	1.3
25	Education	3.2	2.9	3.1	3.2	3.4	3.2	3.0	3.3	3.2	3.0	3.1	3.1	3.4	3.5
27	Arts	1.8	2.0	1.5	1.7	1.7	1.5	1.5	1.6	1.7	1.7	1.8	2.1	2.0	1.9
29	Healthcare practitioner	1.9	2.2	1.8	1.8	1.4	1.7	1.8	1.9	1.8	1.9	2.0	2.3	2.3	2.4
31	Healthcare support	3.2	3.5	3.6	3.5	3.1	3.2	2.9	3.4	3.2	3.6	3.8	3.4	4.0	4.5
33	Protective	2.2	2.4	2.3	2.3	2.7	2.9	2.7	2.3	2.8	2.4	2.6	2.8	2.9	3.0
35	Food	22.7	20.7	21.2	21.6	22.3	22.0	22.1	21.6	21.9	20.9	20.3	19.6	17.9	17.1
37	Building	5.2	6.3	6.6	6.0	6.2	6.1	6.0	5.9	5.7	6.4	6.6	6.0	5.8	6.5
39	Personal	5.5	5.9	6.3	6.4	7.1	6.4	6.4	6.6	6.4	6.5	6.6	7.1	7.3	7.3
41	Sales	11.3	11.5	13.4	14.7	15.6	15.8	16.0	15.9	15.2	15.6	14.9	13.8	13.0	12.5
43	Office	6.8	7.3	8.2	8.2	7.5	8.4	7.7	7.5	7.6	8.0	8.5	8.2	8.4	8.5
45	Farming	4.6	4.6	4.1	3.5	3.3	3.2	3.7	3.1	3.3	3.2	3.0	3.1	4.3	3.8
47	Construction	4.3	3.1	3.3	2.8	2.9	2.9	2.8	2.6	2.8	2.9	2.9	3.1	3.2	3.4
49	Installation	2.1	2.2	1.8	1.8	2.0	2.2	2.3	2.4	2.3	2.1	2.0	2.3	2.2	2.5
51	Production	5.7	6.5	5.4	5.2	4.3	4.9	5.1	4.7	5.0	4.7	4.4	4.7	4.9	4.8
53	Transportation	5.8	5.9	6.6	6.6	6.5	6.7	6.1	6.3	6.4	6.5	6.5	6.7	7.3	7.0

Note: This table presents the average fraction of employment in each occupation who earn at or below 110 percent of the effective minimum wage. Effective level will correspond to the geographical location of the household in the CPS. For every year, we have averaged the fraction of employment across states and four quarters.

TABLE 3: IMPACT OF MINIMUM WAGE ON STOCK AND FLOW OF VACANCIES

	log (Vacancies)			log (New Vacancies)		
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\log(MW_{t-2})$*At-Risk			0.060			0.066
			(0.127)			(0.140)
$\log(MW_{t-1})$*At-Risk		0.063	0.100		-0.001	0.009
		(0.104)	(0.071)		(0.090)	(0.085)
$\log(MW_{t})$*At-Risk	-0.241***	0.011	-0.060	-0.215**	0.031	-0.027
	(0.083)	(0.086)	(0.066)	(0.080)	(0.083)	(0.067)
$\log(MW_{t+1})$*At-Risk		-0.355***	-0.076		-0.291***	-0.068
		(0.109)	(0.066)		(0.096)	(0.079)
$\log(MW_{t+2})$*At-Risk			-0.322**			-0.260*
			(0.125)			(0.132)
Fixed Effects						
County x Time	Yes	Yes	Yes	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Occupation x Time	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	51	51	51	51	51	51
Observations	2,930,908	2,834,751	2,729,919	2,752,397	2,668,600	2,570,188
R-squared	0.921	0.922	0.922	0.928	0.929	0.930

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: This table reports OLS regressions for the dependent variable log(vacancies) for each occupation o, in county c at time t (quarterly). Columns (1) - (3) display results for the stock of vacancies and the remaining columns report the regressions results for new job openings (vacancies that has been posted within the past 30 days). Standard errors are clustered by state

TABLE 4: IMPACT OF MINIMUM WAGE ON VACANCIES - DinD SPECIFICATION

	Total Vacancies in At-Risk Occupations				Total Vacancies in Other Occupations			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(MW_t)$	-0.002	0.005	-0.115	-0.214	0.417***	0.421***	0.388**	0.361
	(0.192)	(0.188)	(0.194)	(0.235)	(0.149)	(0.147)	(0.168)	(0.217)
Unemployment Rate_t		-0.039***				-0.027***		
		(0.006)				(0.005)		
Unemployment Rate_{t-4}			-0.029***				-0.020***	
			(0.005)				(0.005)	
Unemployment Rate_{t-8}				-0.019***				-0.016***
				(0.004)				(0.005)
Unemployment Rate_{t-12}								
Fixed Effects								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	51	51	51	51	51	51	51	51
Observations	168,196	168,104	156,274	144,171	170,865	170,773	158,505	146,194
R-squared	0.946	0.947	0.951	0.953	0.951	0.952	0.954	0.956

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for the dependent variable log(vacancies)for at-risk occupations and the others separately following the specification in equation (2) in the text. Standard errors are clustered by state, and fixed effects are for county and time only.

TABLE 5: IMPACT OF MINIMUM WAGE ON VACANCIES - ADJACENT BORDER COUNTY SAMPLE

	log (Vacancies)		
Dependent Variable	(1)	(2)	(3)
$\log(MW_{t-2})$*At-Risk			-0.035
			(0.118)
$\log(MW_{t-1})$*At-Risk		-0.158	-0.056
		(0.116)	(0.101)
$\log(MW_{t})$*At-Risk	-0.246**	0.031	-0.032
	(0.117)	(0.108)	(0.106)
$\log(MW_{t+1})$*At-Risk		-0.172	0.085
		(0.127)	(0.084)
$\log(MW_{t+2})$*At-Risk			-0.289**
			(0.132)
Fixed Effects			
County x Time	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes
Pair x Occupation x Time	Yes	Yes	Yes
Clusters	218	218	218
Observations	1,948,098	1,887,506	1,817,610
R-squared	0.965	0.965	0.966

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for the dependent variable log(vacancies) for each occupation o, in county c of county-pair, *p,* at time t (quarterly). Standard errors are clustered by state-borders

TABLE 6: IMPACT OF MINIMUM WAGE ON ROUTINE JOBS

	log (Vacancies)		
Dependent Variable	(1)	(2)	(3)
$\log(MW_{t-2})$*At-Risk*RM			-0.596***
			(0.162)
$\log(MW_{t-1})$*At-Risk*RC			0.037
			(0.093)
$\log(MW_{t-1})$*At-Risk*NRM			-0.321**
			(0.133)
$\log(MW_{t})$*At-Risk	-0.241***	-0.321**	
	(0.083)	(0.133)	
$\log(MW_{t})$*At-Risk*Routine		0.149	
		(0.139)	
Fixed Effects			
County x Time	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes
Occupation x Time	Yes	Yes	Yes
Clusters	51	51	51
Observations	2,930,908	2,930,908	2,930,908
R-squared	0.921	0.921	0.921

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for the dependent variable log(vacancies) for each occupation o, in county c at time t (quarterly). The interaction term Routine indicates whether the occupation is a routine one. RM, RC and NRM, refer to a slightly finer classification of 2-digit occupations by task content, where R stands for Routine, M for Manual, C for cognitive and NR for Non-routine. The omitted occupational group in column (3) is the non-routine cognitive group (SOC-11 through SOC-29. Note that this group does not have any at-risk occupations.

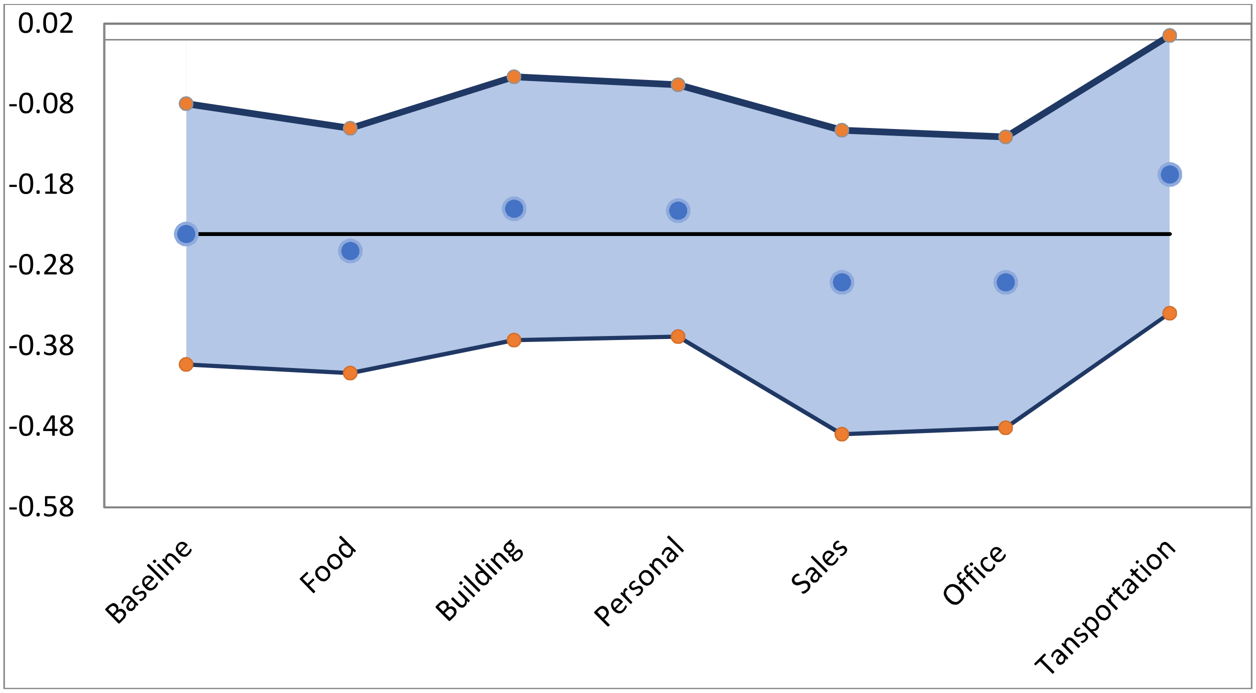

Figure 4: Estimates from baseline specification with at-risk occupations removed from sample one by one.

TABLE 7: ROBUSTNESS - MEASUREMENT OF VACANCY DATA

Dependent Variable	log (V) (1)	$\log(V + \sqrt{V^2+1})$ (2)	log(V+1) (3)
$\log(MW_t)$*At-Risk	-0.241***	-0.250***	-0.227***
	(0.083)	(0.085)	(0.077)
Fixed Effects			
County x Time	Yes	Yes	Yes
County x Occupation	Yes	Yes	Yes
Occupation x Time	Yes	Yes	Yes
Clusters	51	51	51
Observations	2,930,908	3,974,630	3,974,630
R-squared	0.921	0.941	0.950

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table reports OLS regressions for three different transformations of the dependent variable vacancies for each occupation o, in county c at time t (quarterly). The first column repeats the baseline result where we transform vacancy level with a simple logarithmic function. The second column use a transformation with inverse-hyperbolic sine function and the last column renormalizes the 'zero' observations by adding 1 before logarithmic transformation.